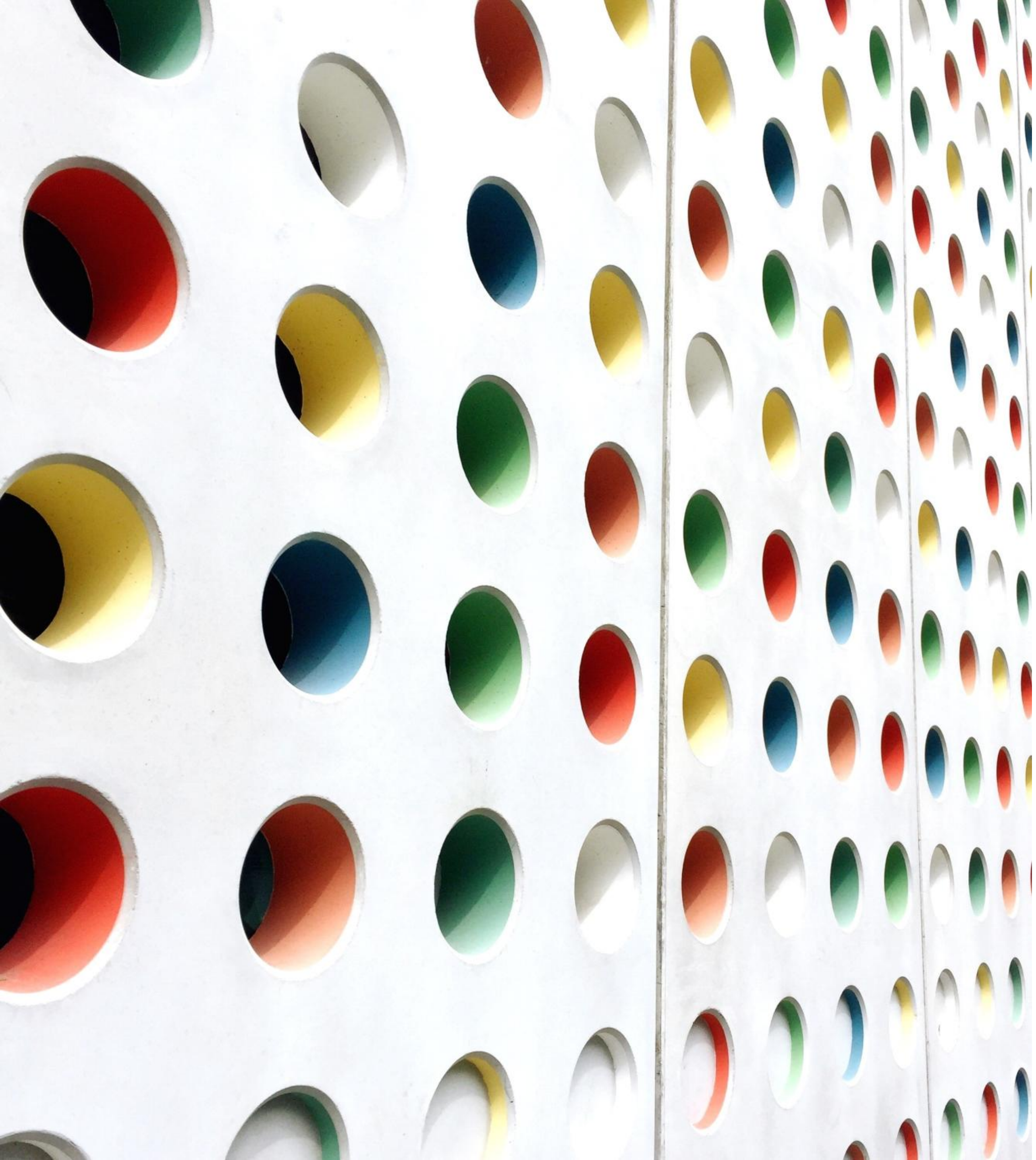


Does your Phone Know if you are Depressed?

ML TLACHAC

ASSISTANT PROFESSOR OF DATA SCIENCE

INFORMATION SYSTEMS & ANALYTICS DEPT.

BRYANT UNIVERSITY

About Me: Prof Tlachac

(kla - atch)

Data Science MS & PhD from WPI

I teach natural language processing, data mining, programming, and capstones

mltlachac@bryant.edu, BELC S229C

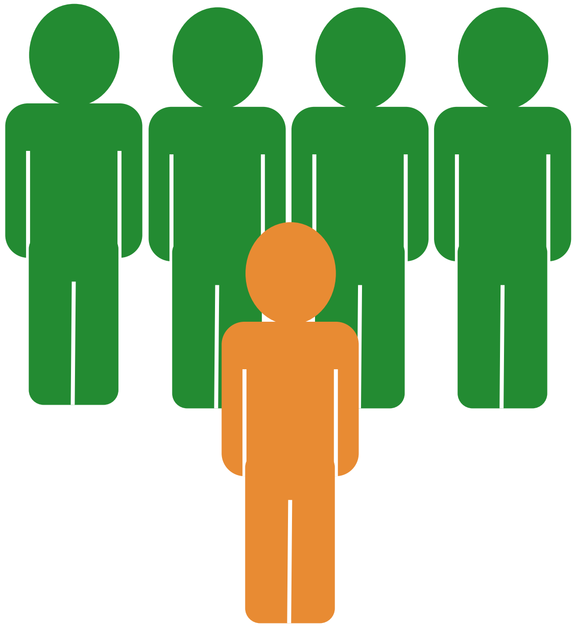
My hobbies include Kakuru puzzles, Krav Maga, stand-up comedy, writing, and walking my dog

Mental Illnesses are Prevalent and Costly

Annually, more than

1 in 5

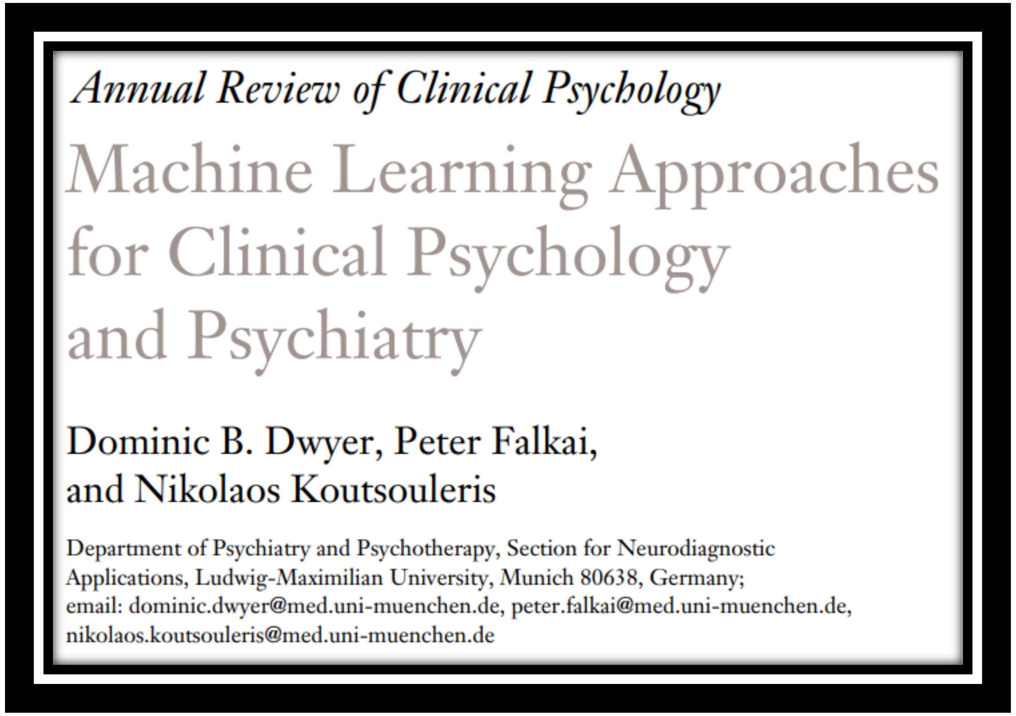
U.S. **adults** experience mental illnesses



“Key substance use and mental health indicators in the united states: Results from the 2021 national survey on drug use and health,” 2022.

Machine Learning in Clinical Psychiatry

- Diagnosis
- Prognosis
- Treatment


Annual Review of Clinical Psychology

Machine Learning Approaches for Clinical Psychology and Psychiatry

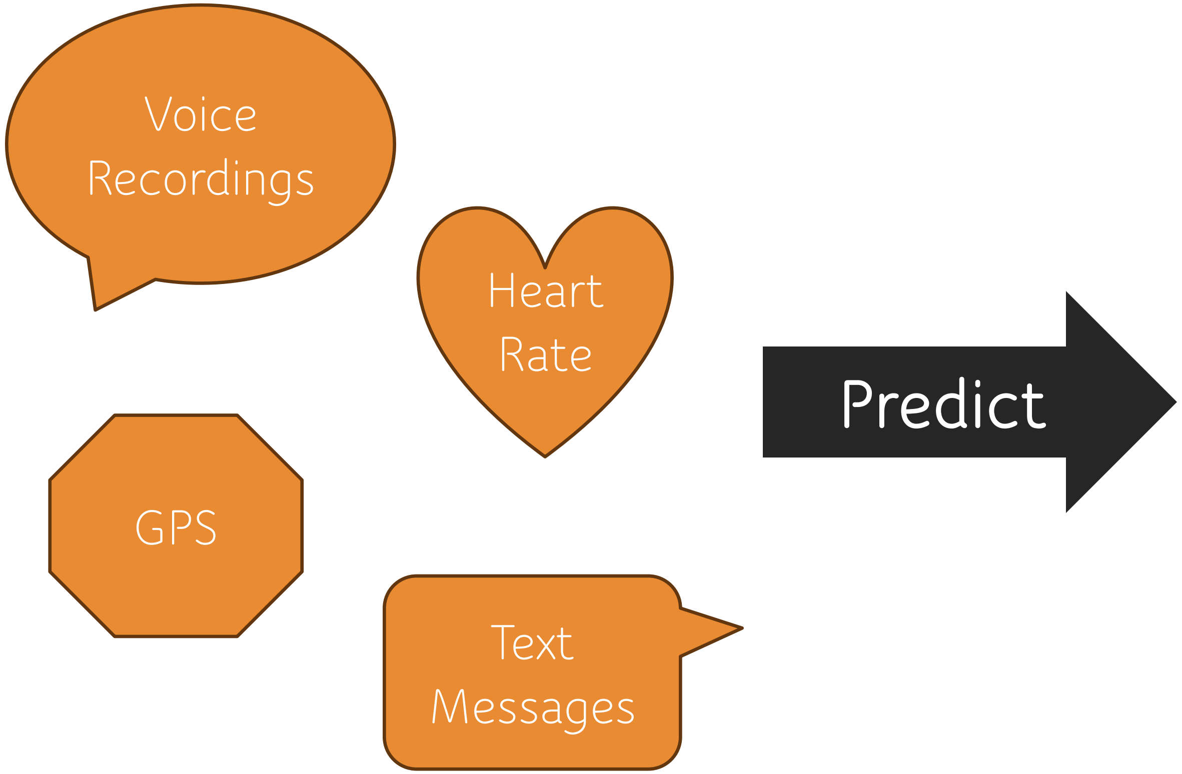
Dominic B. Dwyer, Peter Falkai, and Nikolaos Koutsouleris

Department of Psychiatry and Psychotherapy, Section for Neurodiagnostic Applications, Ludwig-Maximilian University, Munich 80638, Germany; email: dominic.dwyer@med.uni-muenchen.de, peter.falkai@med.uni-muenchen.de, nikolaos.koutsouleris@med.uni-muenchen.de

Diagnosis: Mental Illness Screening

Facilitates earlier detection

Predict Screening Survey Scores



Over the last *2 weeks*, how often have you been bothered by any of the following problems? (*use "✓" to indicate your answer*)	Not at all	Several days	More than half the days	Nearly every day
1. Little interest or pleasure in doing things	0	1	2	3
2. Feeling down, depressed, or hopeless	0	1	2	3
3. Trouble falling or staying asleep, or sleeping too much	0	1	2	3
4. Feeling tired or having little energy	0	1	2	3
5. Poor appetite or overeating				
6. Feeling bad about yourself—or that you are ... have let yourself or your family down				
7. Trouble concentrating on things, such as rea... newspaper or watching television				
8. Moving or speaking so slowly that other peo... have noticed. Or the opposite—being so fig... restless that you have been moving around ... than usual				
9. Thoughts that you would be better off dead, ... hurting yourself				

Over the last two weeks, how often have you been bothered by the following problems?	Not at all	Several days	More than half the days	Nearly every day
1. Feeling nervous, anxious, or on edge	0	1	2	3
2. Not being able to stop or control worrying	0	1	2	3
3. Worrying too much about different things	0	1	2	3
4. Trouble relaxing	0	1	2	3
5. Being so restless that it is hard to sit still	0	1	2	3
6. Becoming easily annoyed or irritable	0	1	2	3
7. Feeling afraid, as if something awful might happen	0	1	2	3

Kroenke K, Spitzer RL, Williams JB. The PHQ-9: validity of a brief depression severity measure. Journal of general internal medicine. 2001
Spitzer RL, Kroenke K, Williams JB, Löwe B. A brief measure for assessing generalized anxiety disorder: the GAD-7. Archives of internal medicine. 2006

PHQ-9 for Depression Screening

Sum the 9 question scores:

- 0-4 asymptomatic
- 5-9 mild
- 10-14 moderate
- 15-19 moderately severe
- 20+ severe

Kroenke K, Spitzer RL, Williams JB. The PHQ-9: validity of a brief depression severity measure. Journal of general internal medicine. 2001

Over the last *2 weeks*, how often have you been bothered by any of the following problems? *(use "✓" to indicate your answer)*	Not at all	Several days	More than half the days	Nearly every day
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5. Poor appetite or overeating	0	1	2	3
6. Feeling bad about yourself—or that you are a failure or have let yourself or your family down	0	1	2	3
7. Trouble concentrating on things, such as reading the newspaper or watching television	0	1	2	3
8. Moving or speaking so slowly that other people could have noticed. Or the opposite—being so figety or restless that you have been moving around a lot more than usual	0	1	2	3

Screening with Text Message Logs

- Screening with Log Content
- Screening with Log Counts
- Screening with Log Time Series
- Screening with Log Distributions

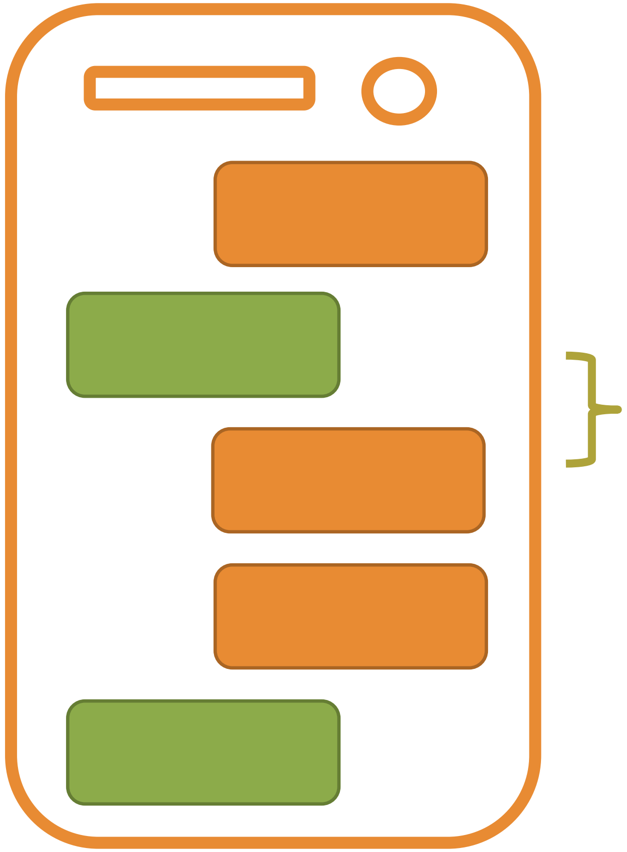
Datasets of SMS text logs

Dataset	Start	End	Participants	Sent	Replies	Follow-ups	Received
SLOTH	July 2021	Oct. 2021	31	5,694	3,086 (54.2%)	2,513 (44.1%)	5,478
DepreST-CAT	Dec. 2020	April 2021	49	4,281	2,396 (56.0%)	1,763 (41.2%)	4,383

SMS text logs were retrospectively harvested from Prolific crowdsourced workers

ML Tlachac et al, "Symptom Detection with Text Message Log Distributions…", ACM IMWUT, 2024; ML Tlachac et al, "DepreST-CAT", ACM IMWUT, 2022;
Palan & Schitter, "Prolific", J of Behavioral and Experimental Finance, Elsevier, 2018

Reply Latency for Mental Illness Screening



Number of seconds between receiving and sending a text message

ML Tlachac et al, "Symptom Detection with Text Message Log Distributions..", ACM IMWUT, 2024

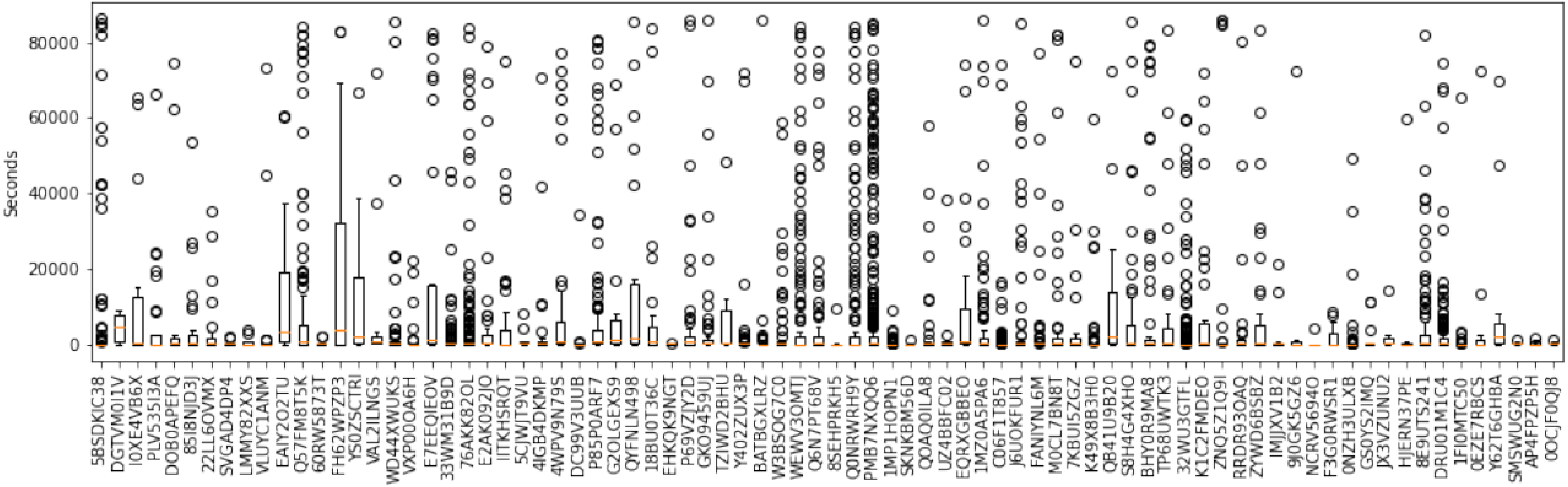
How Did I Think of Using Reply Latency?

I have privacy concerns with using text content so I'm going to work with text sending patterns next.

Oh, like how long it takes someone to reply to a text message?

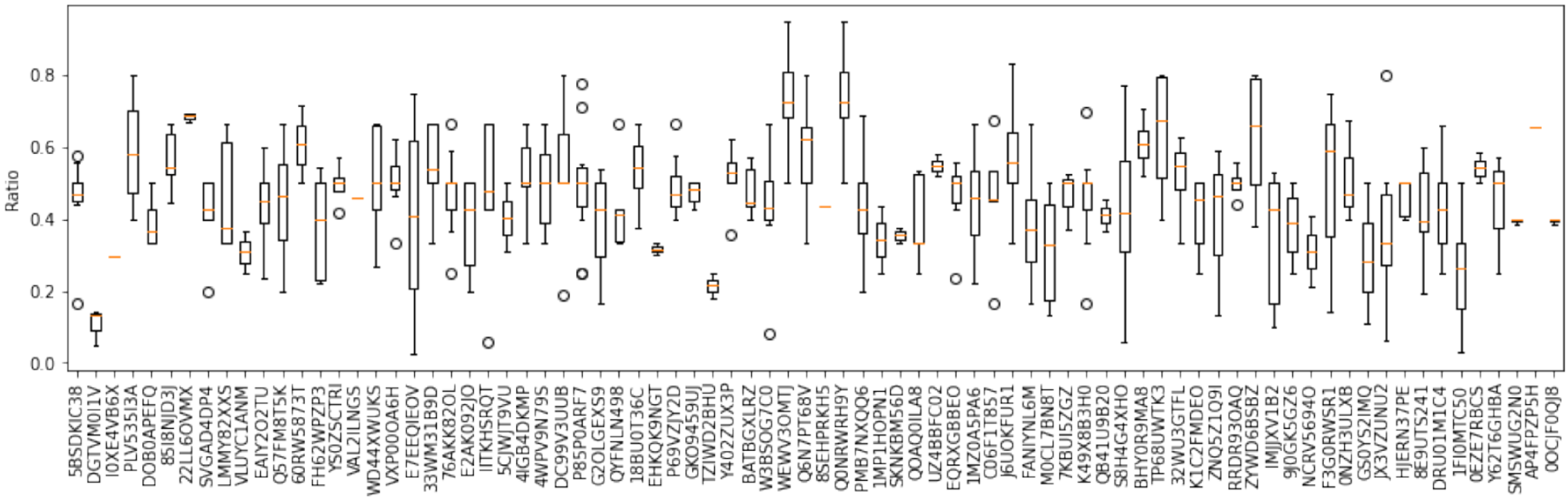
Not what I meant ...
but that's a great idea!

Reply Latency for Each Participant

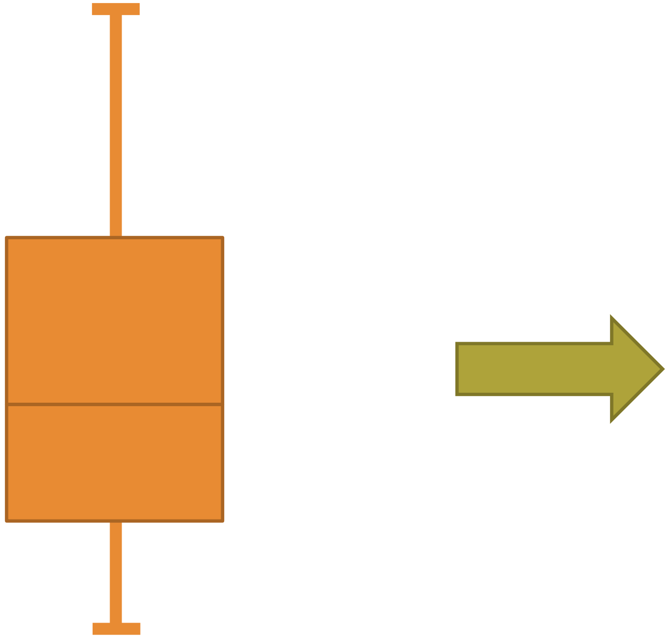


ML Tlachac et al, “Symptom Detection with Text Message Log Distributions…”, ACM IMWUT, 2024

Conversation Ratio for Each Participant



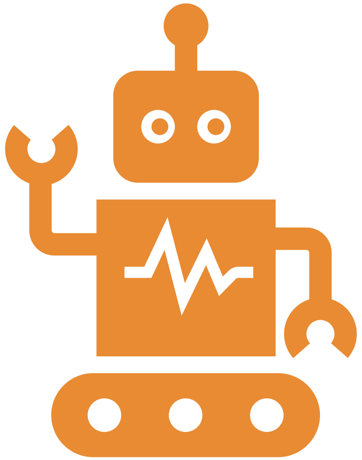
Distribution Features



1. 10% quantile latency
2. 25% quantile latency
3. 50% quantile latency
4. 75% quantile latency
5. 90% quantile latency

Predictive Models

1. 10% quantile latency
2. 25% quantile latency
3. 50% quantile latency
4. 75% quantile latency
5. 90% quantile latency



1 = positive depression screening

0 = negative depression screening

Detection of Depression Symptoms

Item	Symptom	Type	Method	PCs	Kernel	Bal. Acc.	Sens.	Spec.
PHQ-9 Q1	Little Interest	Conv. Ratio	XG	4	linear	0.72	0.62	0.81
PHQ-9 Q2	Feeling Depressed	Reply Latency	kNN	4	RBF	0.74	0.69	0.80
PHQ-9 Q3	Trouble Sleeping	All	Ada	7	linear	0.66	0.69	0.62
PHQ-9 Q4	Feeling Tired	Reply Latency	Ada	1	RBF	0.72	0.77	0.67
PHQ-9 Q5	Appetite Irregularities	Conv. Ratio	XG	5	RBF	0.74	0.69	0.80
PHQ-9 Q6	Feeling Failure	Reply Latency	XG	2	linear	0.70	0.62	0.77
PHQ-9 Q7	Trouble Concentrating	Conv. Ratio	XG	5	RBF	0.69	0.72	0.66
PHQ-9 Q8	Movement Irregularities	Conv. Ratio	Ada	5	RBF	0.70	0.50	0.91
PHQ-9 Q9	Self-harm Thoughts	Reply Latency	kNN	1	both	0.64	0.59	0.70

Detection of Anxiety Symptoms

Item	Symptom	Type	Method	PCs	Kernel	Bal. Acc.	Sens.	Spec.
GAD-7 Q1	Feeling Anxious	Reply Latency	XG	2	RBF	0.71	0.70	0.72
GAD-7 Q2	Uncontrollable Worrying	All	Ada	8	linear	0.73	0.70	0.77
GAD-7 Q3	Excessive Worrying	Reply Latency	XG	2	linear	0.72	0.74	0.71
GAD-7 Q4	Trouble Relaxing	Reply Latency	Ada	3	RBF	0.78	0.78	0.78
GAD-7 Q5	Restlessness	All	Ada	5	RBF	0.71	0.62	0.79
GAD-7 Q6	Easily Annoyed	Reply Latency	Ada	3	linear	0.73	0.65	0.80
GAD-7 Q7	Feeling Afraid	All	SVC	2	RBF	0.76	0.77	0.76

Repeated on DemonicSalmon Dataset

72 undergraduate students	University of Virginia	Spring semester of 2016
2 weeks of passive sensing data	Social anxiety screening scores	Depression screening scores

M. Boukhechba, A. Daros, K. Fua, P. Chow, B. Teachman, and L. Barnes, “Demonicsalmon: Monitoring mental health and social interactions of college students using smartphones,” Smart Health, vol. 9, pp. 192-203, 2018.

Results were even Better!

TLACHAC AND OGDEN. "STUDENT MENTAL HEALTH SCREENING WITH TEXT MESSAGE METADATA", ICMLA 2024

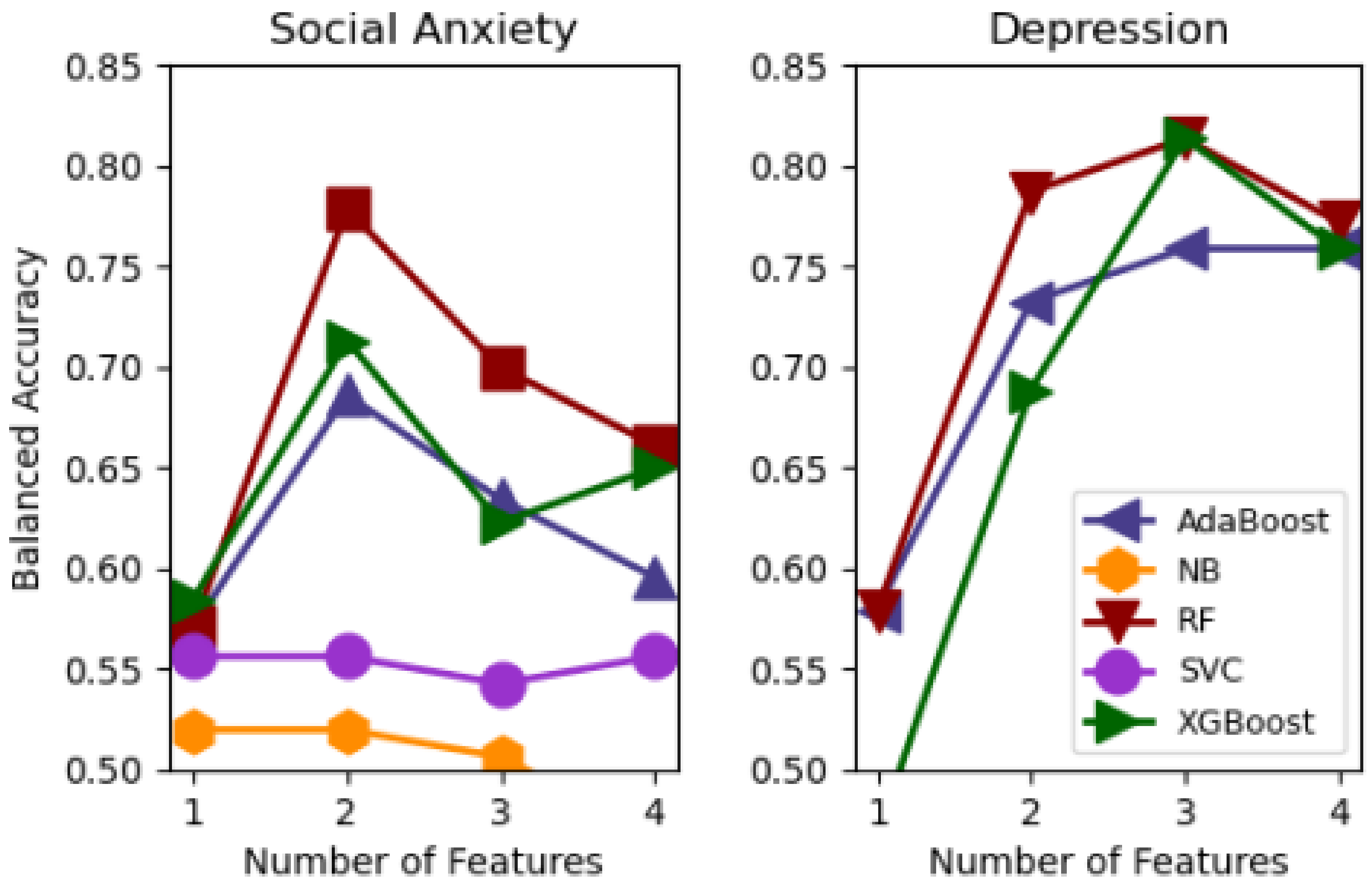
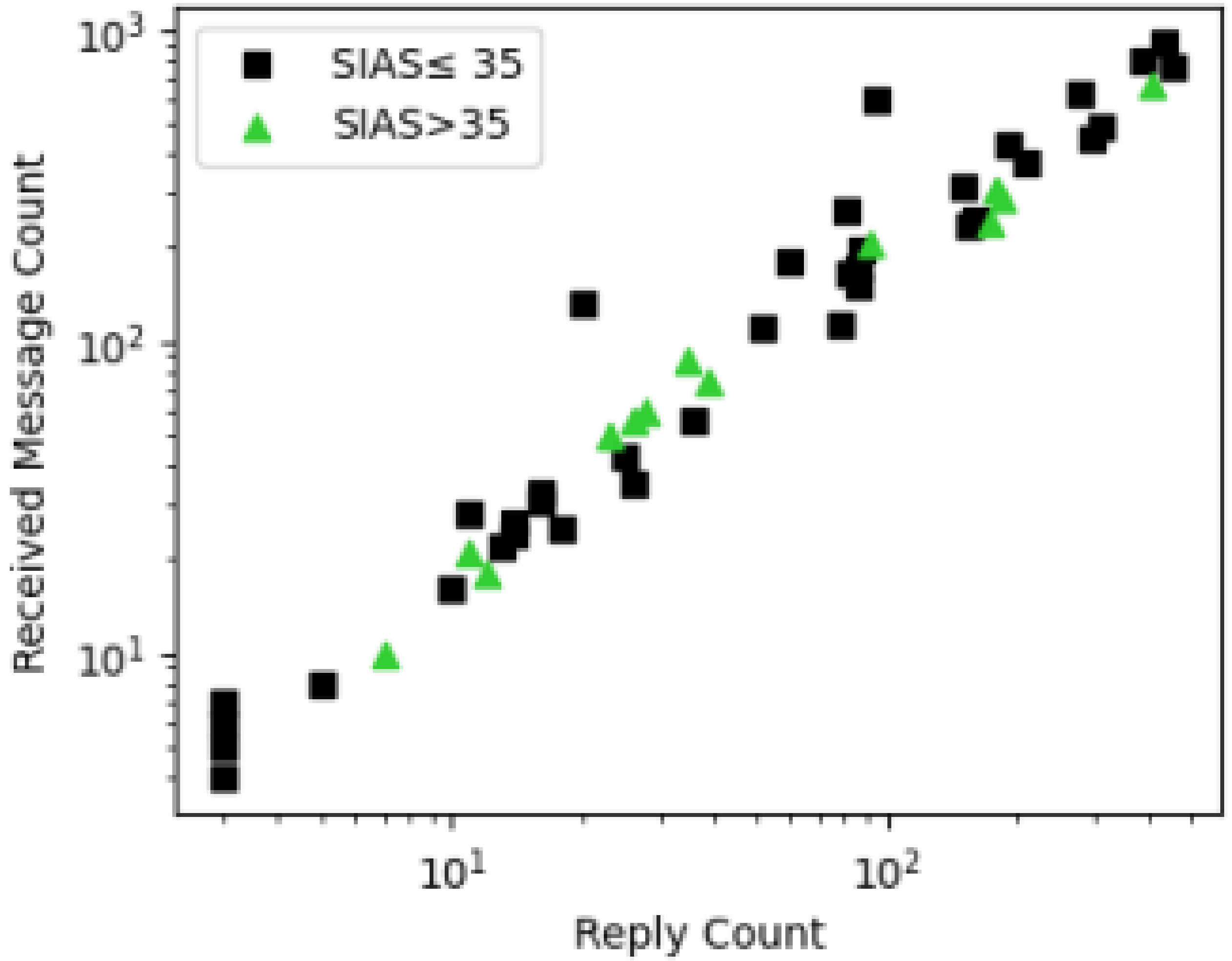


Fig. 5. Screening results with the most successful models. The social anxiety screening models used the basic count feature set while the depression screening models used the consecutive message distribution feature set.



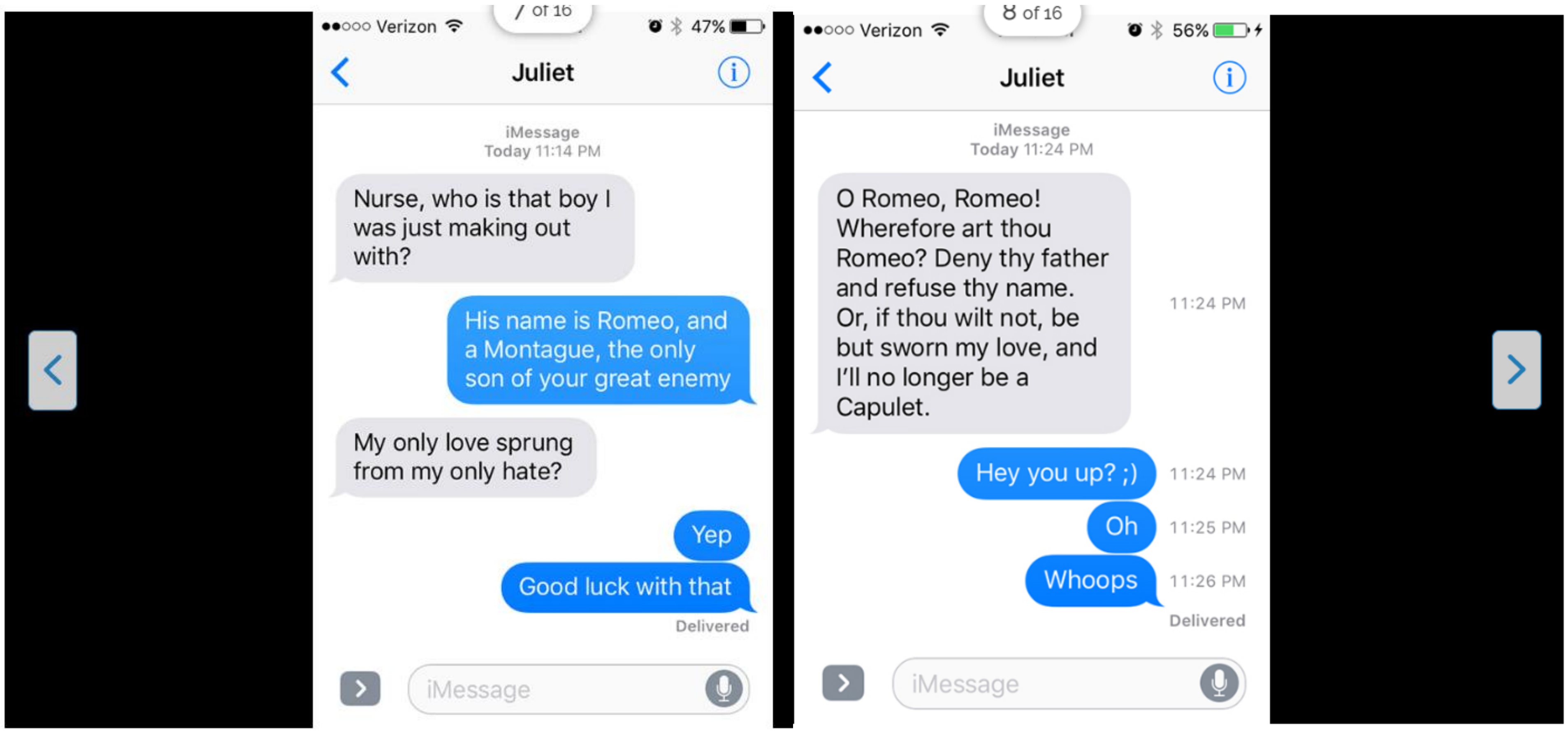
Important Features for Social Anxiety Screening

TLACHAC AND OGDEN. “STUDENT MENTAL HEALTH SCREENING WITH TEXT MESSAGE METADATA”, ICMLA 2024

Screening with Text Message Logs

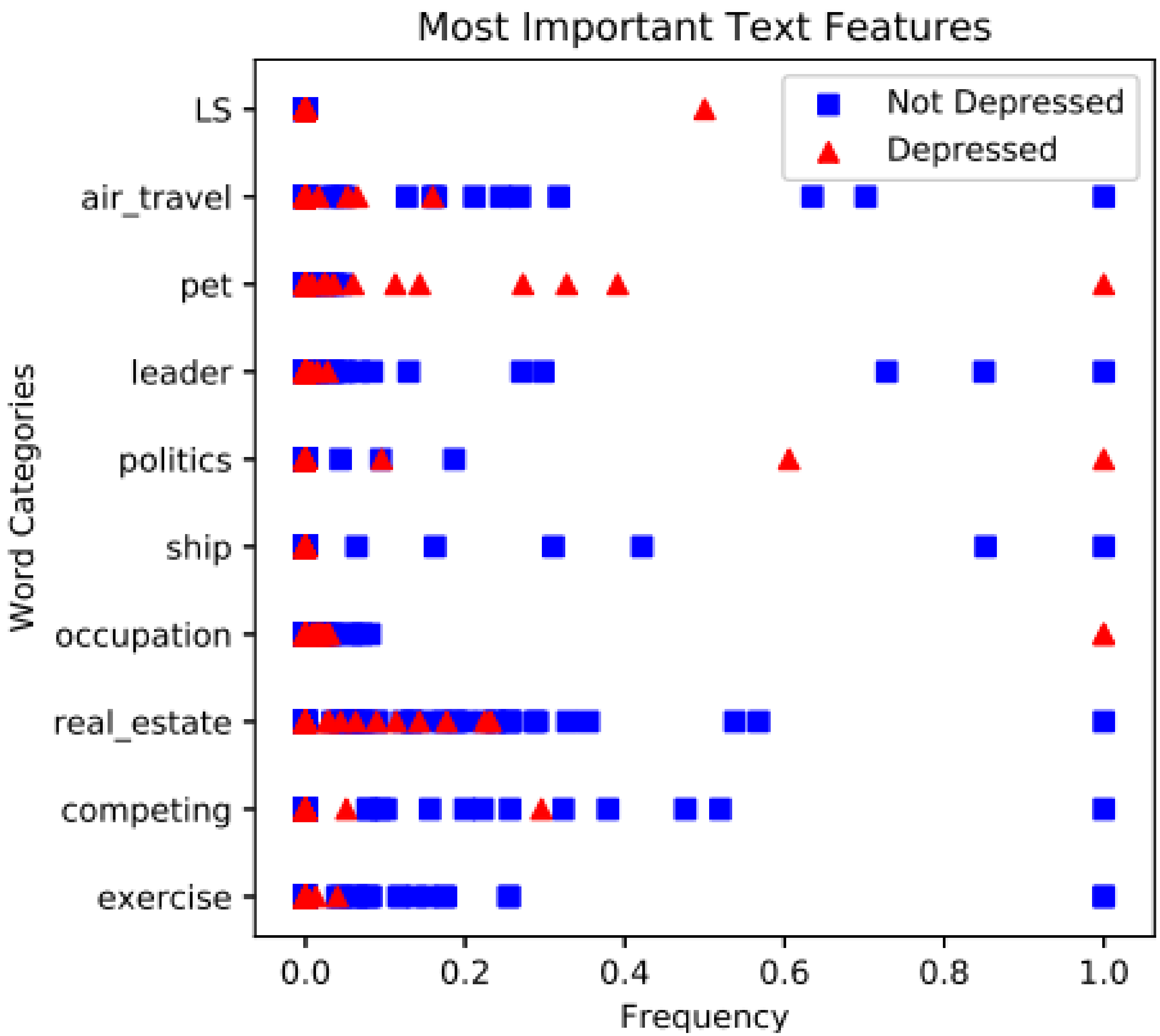
- Screening with Log Content
- Screening with Log Counts
- Screening with Log Time Series
- Screening with Log Distributions

Language Differs by Platform



credit: SparkNotes/Elodie

Why would depressed people talk about pets more?



Most Important Features Across Text Types

Communication and vacation related words were useful in the depression screening models for all three types of text

T Zhao and ML Tlachac, Bayesian optimization with tree ensembles to improve depression screening on textual datasets. IEEE Transactions on Affective Computing, 2024

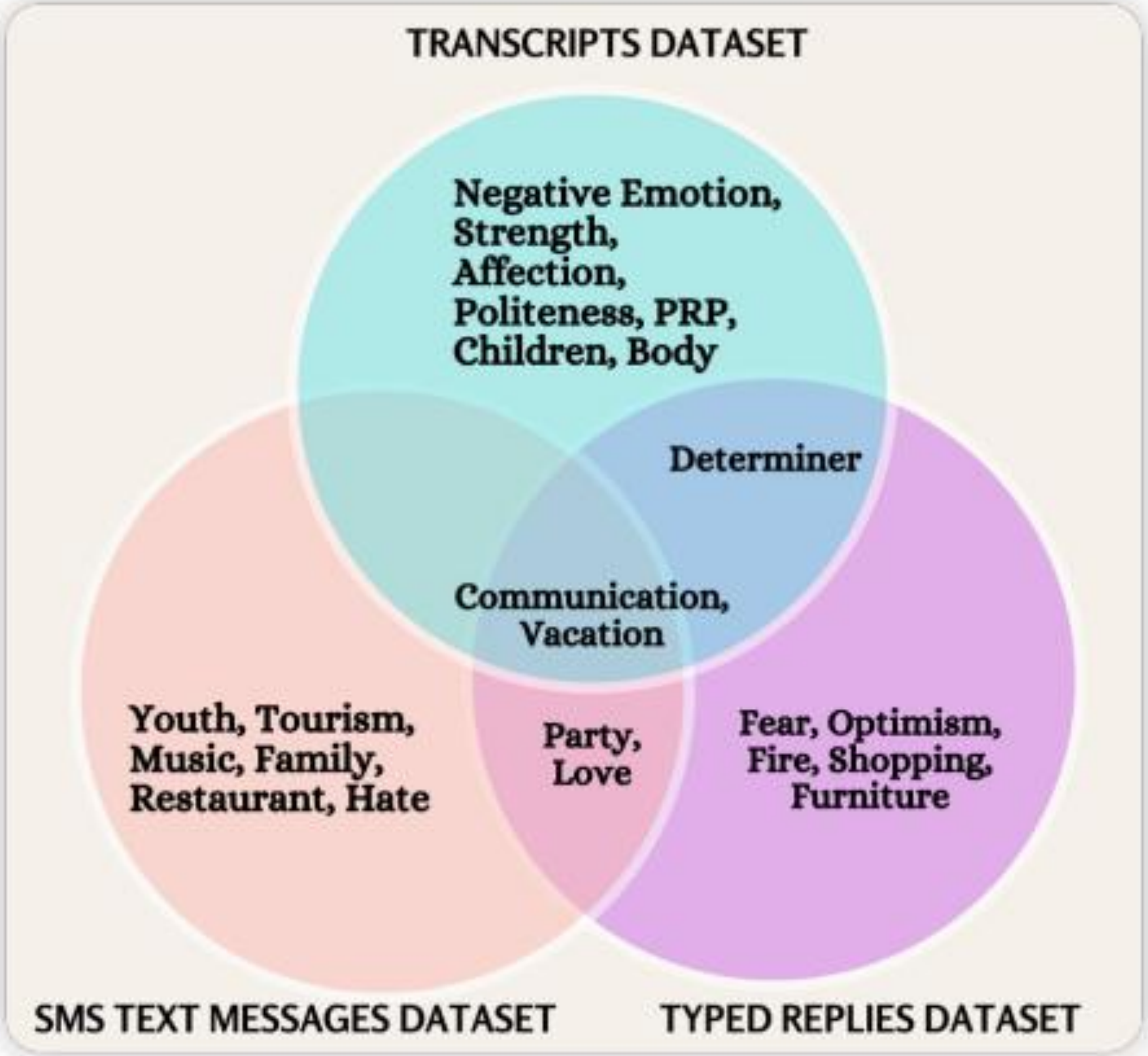


Fig. 5. Comparison of the 10 most important features across three datasets.

My Most Recent Papers

ML Tlachac, Tingting Zhao, Allison Papini, Terri Hasseler, Suhong Li, David Gannon, and Philip Lombardi. "**Artificial Intelligence Chatbot Perception and Use Across Campus**." *Journal of Computer Information Systems* (2025)

ML Tlachac, Michael V. Heinz, Anastasia C. Bryan, Arielle LaPreay, Geri Louise Dimas, Tingting Zhao, Nicholas C. Jacobson, and Samuel S. Ogden. "**Datasets of Smartphone Modalities for Depression Assessment: A Scoping Review**." *IEEE Transactions on Affective Computing* (2025).

Artificial Intelligence Chatbot Perception and Use Across Campus

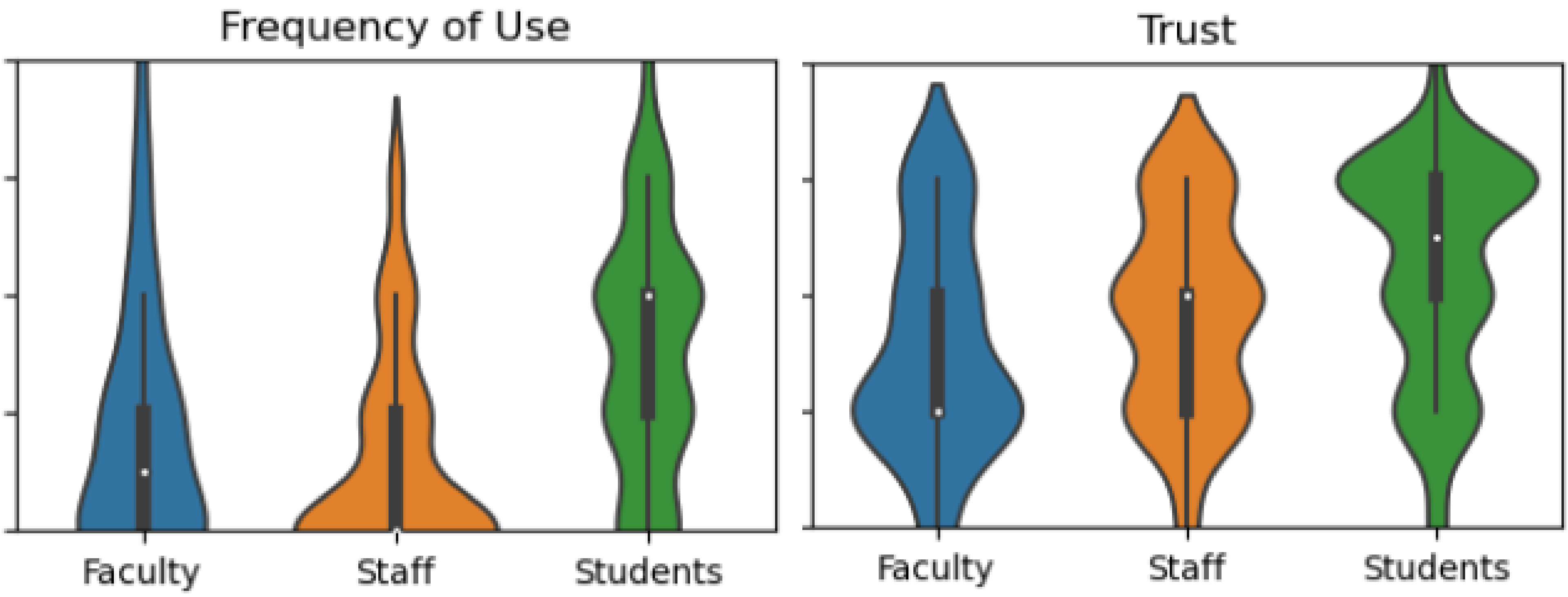
Since the widespread availability of generative Artificial Intelligence (AI) Chatbots, colleges and universities have been grappling with their impact on higher education.

We designed and conducted a survey to capture use and perception of AI Chatbots across the three primary campus populations: faculty ($N = 77$), staff ($N = 110$), and students ($N = 223$).

While all three campus populations had similar scores regarding being first adopter of new technology, they had statistically significantly different scores for seven other 5-point Likert scales regarding AI Chatbot use and perception.

Despite the **differences in their use and perception**, subsequent textual analysis indicates that the **campus populations share similar concerns** about AI Chatbot accuracy, bias, and technology dependency.

Artificial Intelligence Chatbot Perception and Use Across Campus



Datasets of Smartphone Modalities for Depression Assessment: A Scoping Review

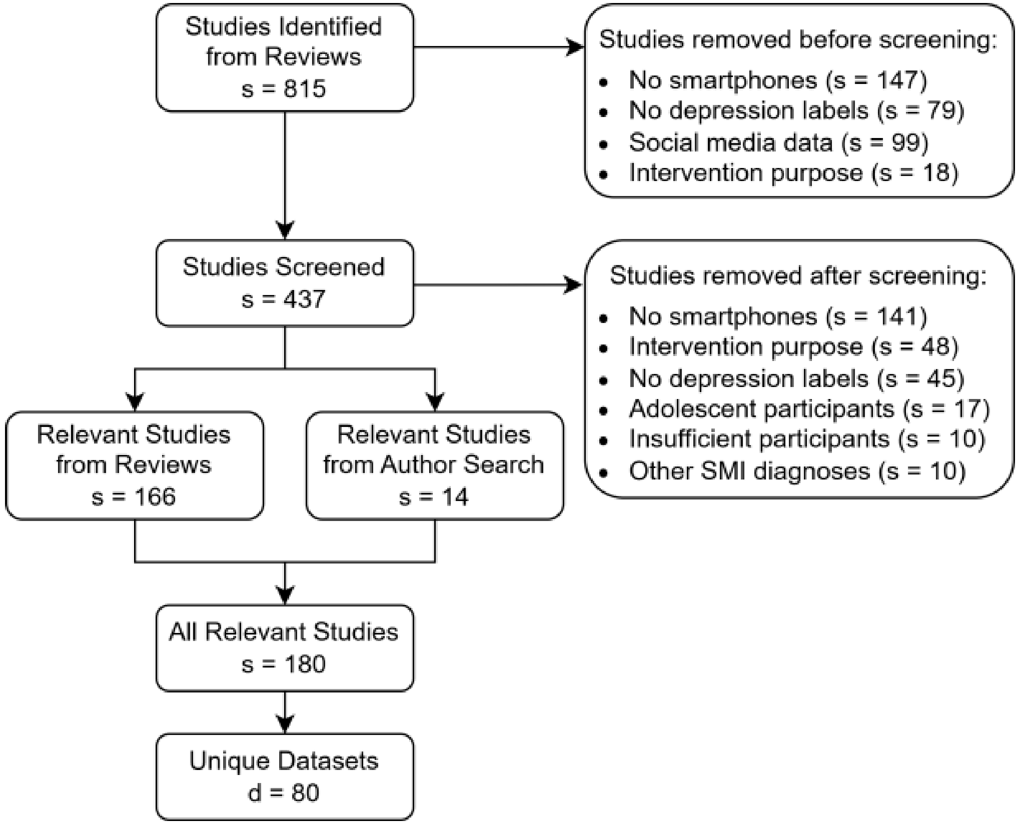


Fig. 1. Flow diagram of the study identification and screening process.

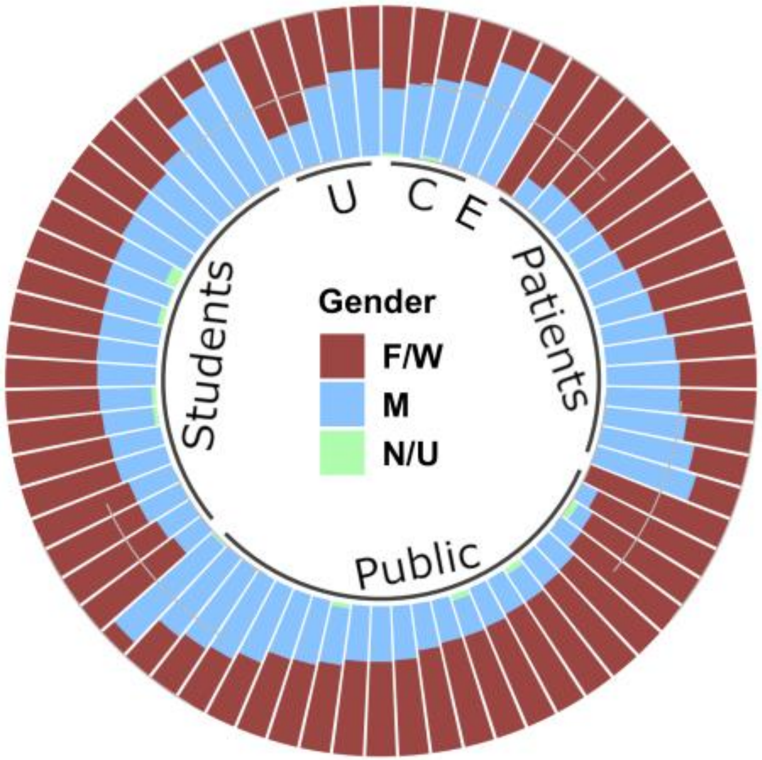


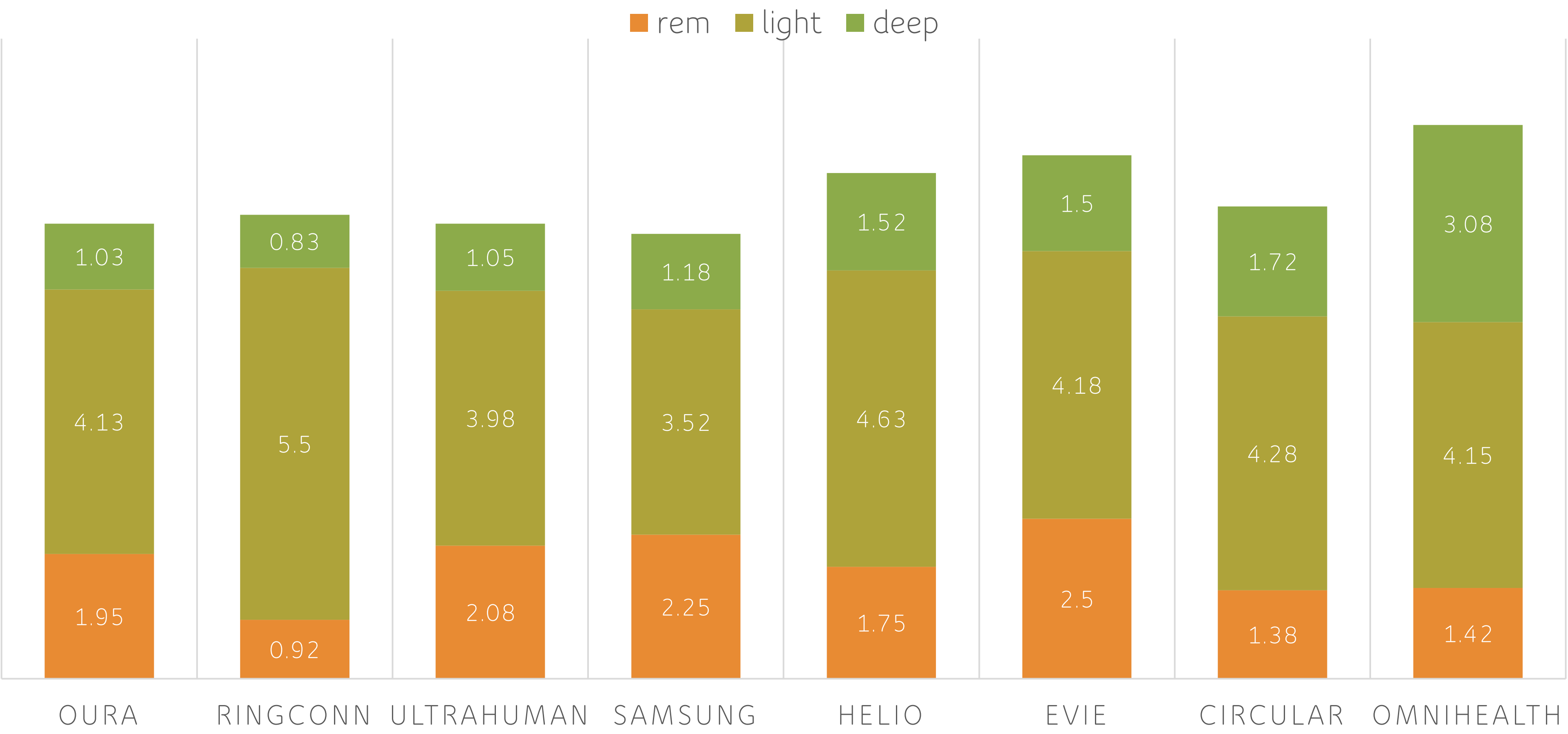
Fig. 3. Gender of the crowdsourced (C), employee (E), patient, public, student, and unknown (U) participant populations. F/W = Female/Woman, M = Male/Man, and N/U = Nonbinary/Unknown.

My Future Research: Smart Rings

I found only one dataset had depression screening scores and smart ring data.

I'm currently testing 8 different smart rings.

Smart Ring Sleep Comparison



Correctly Detected I woke up at 6am:

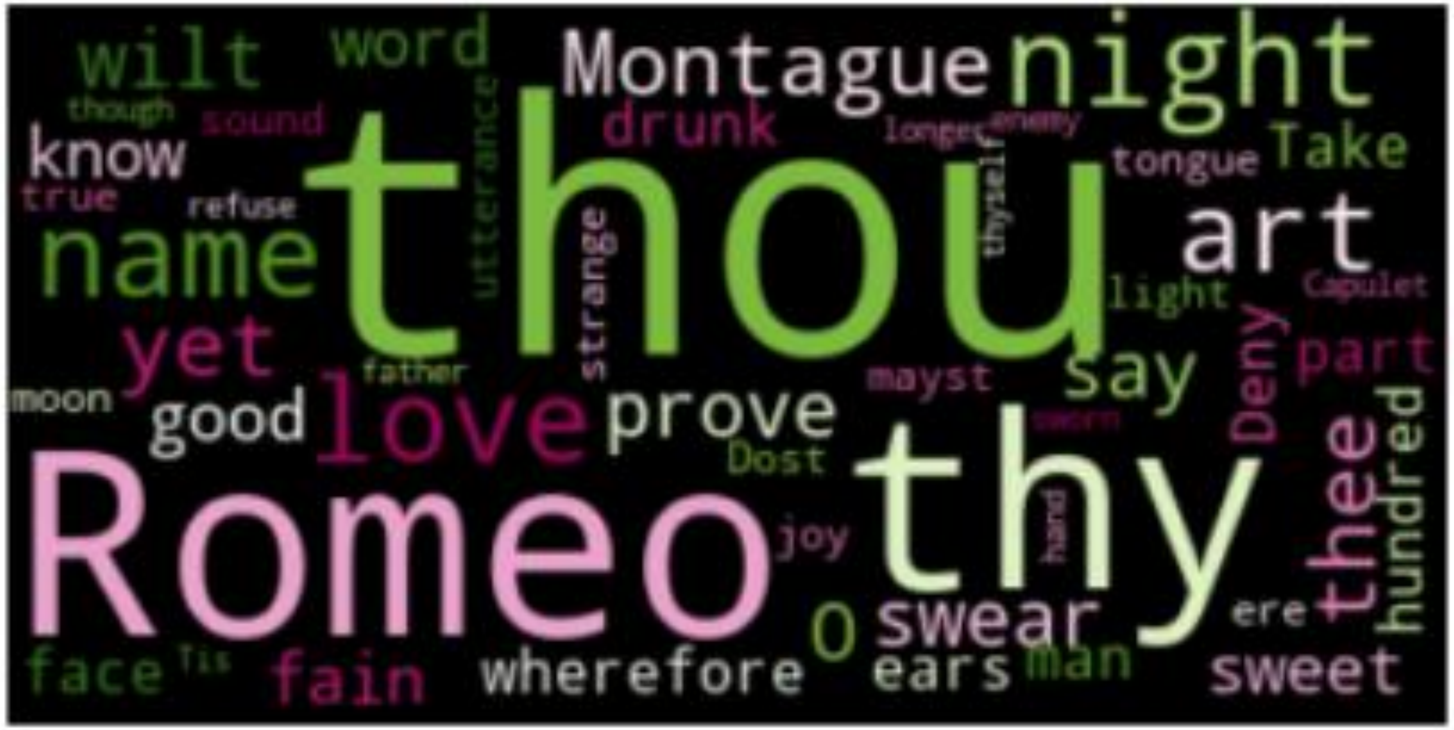
- Ringconn
- Samsung
- Helio
- Circular

Incorrectly recorded I slept until 7:30am:

- Oura
- Ultrahuman
- Omnihealth

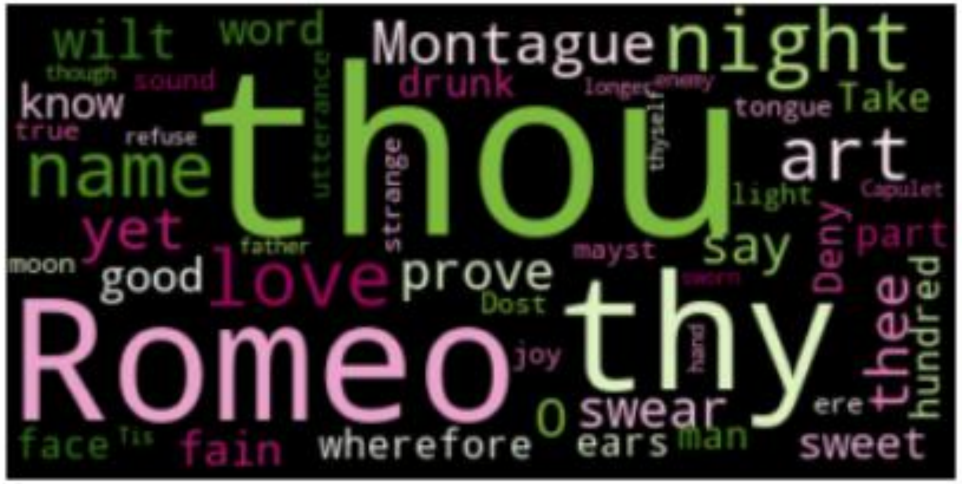
On Another Shakespeare Tangent

- Created word cloud of the famous “balcony scene” when preparing for class
- Noticed Juliet often calls Romeo by name
- How often does Romeo call Juliet by name?



Romeo Rarely Calls Juliet by Name

JULIET



ROMEO

There's a bigger research question about gender politics within character interactions in Shakespeare plays

Questions are Everywhere!

COULD KRISTOFF AND ANNA FROM FROZEN SURVIVE THE FALL OFF THE CLIFF INTO THE SNOW?

I Have Some Questions about the Buses

How short does the ride need to be to encourage filling the bus from front to back?

What personality traits are related to wearing seat belts?

Questions?

MLTLACHAC@BRYANT.EDU